CENTER FOR DECISION RESEARCH

A Theory of Diagnostic Inference:
Contract Final Report

Robin M. Hogarth
University of Chicago
Graduate School of Business
Center for Decision Research

Graduate School of Business
The University of Chicago

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This report summarizes work conducted during the period from February 15, 1987 to July 31, 1990 on the psychology of decision-making processes and provides a chronological sequel to an earlier report (covering the period from October 15, 1983 to February 14, 1987). The central theme underlying the work is that complex judgments and choices result from simple psychological processes that interact with highly variable and complex environments. Thus, the research has been aimed at identifying such processes, describing them by parsimonious mathematical models, and testing their implications in experimental tasks. Three lines of research are described. These involve investigations concerning choice under conditions of risk, ambiguity, and ignorance; belief updating; and the effects of exactingness and incentives on the learning of repetitive decision making tasks. (By exactingness is meant the extent to which failure to make accurate responses during learning is punished by the environment.) Presentation of each of the investigations follows a similar format: statement of issues motivating the research, specification of the

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model and psychological principles underlying the theoretical approach adopted, and summary of the main experimental results. The report concludes by listing technical reports and publications related to the project. These provide detailed information on various aspects of the different investigations.

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Introduction

This report summarizes work conducted during the period from February 15, 1987 to July 31, 1990 on the psychology of decision-making processes and provides a chronological sequel to an earlier report covering the period from October 15, 1983 to February 14, 1987 (Einhorn & Hogarth, 1987). The structure of this report reflects the three major topics under which research has been conducted. However, a discussion of these topics is prefaced by some general remarks emphasizing the central theme underlying the work and the research strategy adopted.

Both the central theme of the work, as well as the general research strategy, are the same as that outlined in the previous report (Einhorn & Hogarth, 1987). They are therefore restated here.

Central theme. The central theme underlying much of the work is that complex judgments and decisions result from simple psychological processes that interact with highly variable and complex environments. In other words, whereas basic psychological processes are quite simple, the complexity of behavior results from the way such processes interact with the complexities of the environment (see Hogarth, 1986). However, it is the complexity of behavior that we seek to elucidate.

Research strategy. Given the above, the research strategy adopted has sought to develop descriptive, quantitative models of judgment and choice by:

1. Identifying basic psychological processes.
2. Developing parsimonious mathematical models of these processes.
3. Constructing tasks and environments in which to test the predictions of the models.
4. Empirically testing the predictions.

Areas of research. Research has been conducted in three areas. These are (a) the psychology of choice with particular reference to decisions made under conditions of ambiguity and ignorance; (b) belief updating; and (c) the effects of exactingness[1] and incentives on learning. The following three sections of this report discuss each of these areas of research. In each section,

[1] The term "exactingness" is explained below.

we first outline the issues motivating the research and the principles underlining our approach to the specific problems. After presenting the models developed for each project, we summarize implications and the major empirical results obtained to date.

Venture Theory and Choice under Ambiguity and Ignorance

One dimension on which laboratory studies of decision making lack ecological validity is that subjects are required to make choices between options for which precise probabilistic information is presented. For example, subjects are asked to make choices between, say, winning $2,000 with probability .8 (and nothing with probability .2), versus a .7 chance of winning $2,400 (and nothing with probability .3). In the real world, however, it is rare that people face such precise choice alternatives. Instead, if probabilistic information is provided, at best it is only likely to be vaguely specified, e.g, "*about* 8 chances in 10 of winning," or "between 70% and 90%." At worst, it is not provided and chances have to be inferred from the context by the decision maker. In previous work (notably Einhorn & Hogarth, 1985), we developed a psychological model of how people take account of vague probabilistic information when estimating probabilities. Research conducted under this heading during the reporting period extended the earlier work in three ways. First, additional experimental tests of the ambiguity model were conducted using scenarios that mimicked real-world situations. Second, the psychological principles behind the ambiguity model were generalized in order to develop a general model of choice which would also handle situations where probabilities are known with precision. Third, a new line of investigation was begun involving situations where no (even vague) probabilistic information was available to subjects. To discuss these developments, it is first appropriate to provide an overview of the ambiguity model.

Overview of ambiguity model

The main psychological assumption underlying the model is that the subjective weights

given to ambiguous probabilities are the end result of a mental anchoring-and-adjustment process. People are assumed to anchor on a particular estimate of the probability and then adjust this by imagining, via a mental simulation process, other values that the probability could take. To illustrate, consider a situation in which you are concerned about the chances of an accident occurring in a new industrial facility. A study conducted by technical experts assesses the risk as $p = .001$, but they have doubts about the precision of this estimate. In the process assumed here, it is postulated that you would first anchor on a given value of probability (e.g., the .001 provided by the experts) and then imagine or "try out" other values the probability could take, both below and above the anchor. Depending on the circumstances (see below), you would not necessarily accord equal weight in imagination to possible values of the probabilities on both sides of the anchor. For instance, in the present example values above the anchor may well weigh more heavily in imagination than those below (the occurrence of accidents might be salient). The resulting weight given to the ambiguous probability is taken to reflect both the initial anchor and the net effect of the mental simulation process and can be written

$$S(p_A) = p_A + (k_g - k_s) \qquad (1)$$

where p_A is the anchor, k_g represents the values and weight accorded in the mental simulation to values of p greater than the anchor, and k_s corresponds to the weighted values below the anchor.

To make these notions operational, one needs to specify (1) how the anchor, p_A, is established, (2) what affects the amount of mental simulation (i.e., the ranges of alternative probability values considered), and (3) what determines the sign or direction of the adjustment process.

(1) In ambiguous circumstances, some initial value of the probability is assumed to be typically available to the decision maker. This may be a figure based on historical data, provided by experts (as in the example above), or selected from memory.

(2) If the decision maker has sufficient knowledge to assign a unique value to the probability there would be little or no mental simulation. When the probability is ambiguous, one

would expect considerable simulation, the extent of which is assumed to be positively related to the amount of perceived ambiguity.

(3) The sign of the adjustment process is determined by the person's attitude toward ambiguity. This could reflect personal dispositions toward optimism or pessimism, but is assumed to depend on situational variables such as the sign or size of outcomes or whether the context of the situation induces caution (as when considering insurance) or playfulness (as when gambling).

The manner in which imagination affects the anchor value, p_A, in the ambiguity model can be shown by depicting the judgmental compromise that results from the anchoring-and-adjustment process as a function of the anchor probability. This is illustrated in the three panels of Figure 1 below.

In interpreting the panels of Figure 1, recall that two forces cause the final judgment to deviate from the anchor. These are the amount of perceived ambiguity and the person's attitude toward ambiguity in the circumstances. The former determines the amount of mental simulation and thus the extent to which the ambiguity function deviates from the diagonal (45^o) line; the more the perceived ambiguity, the greater the deviation. The latter determines the direction of the adjustment and thus the point at which the ambiguity function crosses the diagonal.

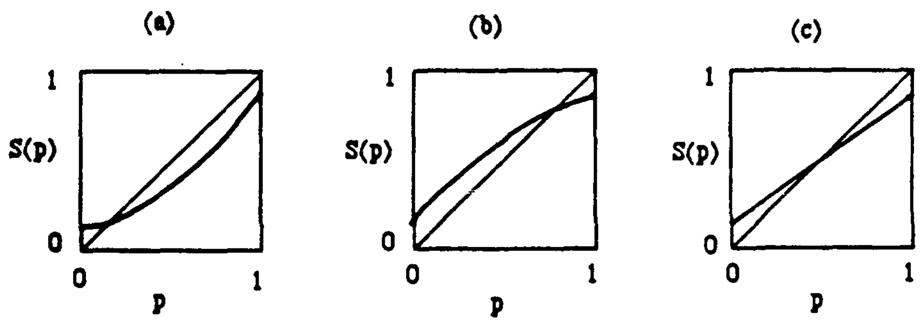

Figure 1: Examples of three "ambiguity" functions

Consider first the extreme anchors of $p_A = 0$ and $p_A = 1$. In both cases, the adjustment can only be in one direction, up for $p_A = 0$ and down for $p_A = 1$, thereby illustrating the fact that the location of p_A places constraints on the ranges of values that can be imagined above and below the anchor. Thus $S(p_A) > p_A$ when $p_A = 0$ and $S(p_A) < p_A$ when $p_A = 1$. In general, $S(p_A)$ will overweight small probabilities and underweight large ones; what changes from situation to situation is the point at which the ambiguity function crosses over the diagonal (45^o) line, i.e., where overweighting changes to underweighting. In Figure 1a, values of the probability below the anchor are weighed in imagination more heavily than those above, and the cross-over point lies below $p_A = .5$. In Figure 1b, values above the anchor are weighted more heavily than those below. Here the cross-over point lies above .5. In Figure 1c, values above and below the anchor are weighted equally such that the crossover occurs at .5.

To summarize, the ambiguity function shows overweighting of small anchor values but underweighting of larger ones. The point at which the function changes from over- to underweighting depends on the person's attitude toward ambiguity. For example, assuming that people are generally cautious in the face of risk, the ambiguity function would resemble that shown in Figure 1a if the decision maker is concerned with the possibility of obtaining a positive outcome. On the other hand, when faced with the possibility of a loss (e.g., when assessing the risk of a new technology), the function would be better represented by Figure 1b. This is because caution induces greater concern for possible values of the probability lying below rather than above the anchor in the case of potential gains, whereas the contrary holds for losses. We also argue that the location of the cross-over point will be affected by the degree of caution engendered by the situation. Thus, when facing the ambiguous chance of gaining a very large sum of money, the cross-over point will be closer to $p_A = 0$ than in a case where a small sum is involved. Similarly, when faced with a large potential loss, the cross-over point will be closer to $p_A = 1$ than in a situation involving a small loss.

As noted in the previous report, this model handles many of the paradoxes of choice theory and, in particular, that posed by Ellsberg.

Additional empirical results

In work completed during the period under review, further features of the model were exploited:

(1) Further analyses were completed of a data base of questionnaires collected from practicing actuaries -- see Hogarth and Kunreuther (1989; 1990). The results of these studies were substantially in agreement with the theoretical predictions of the ambiguity model (both in terms of quantitative outputs and some process details), and provided important information concerning the conditions under which ambiguity does and does not affect the relative thickness of insurance markets. In addition to providing these substantive conclusions concerning the market for insurance, these results are important in that, because the subjects were professionals operating in their area of expertise, they speak to the ecological validity of the model.

(2) Experimental tests of the model were extended to scenarios involving bargaining over terms in the purchase of industrial goods (using business executives as subjects), and the manner in which ambiguity might affect the tendency for different parties to a lawsuit to either settle out of court or go to trial. In both of these situations, predictions were made by recognizing that ambiguity would differentially affect estimations of uncertainty made by persons with different roles in a transaction or dispute (e.g., plaintiffs vs. defendants). This occurs largely because different roles can "frame" the probabilities of the same events as involving potential gains or losses -- see Figure 1. The differential predictions of the model were borne out by the experimental results -- see Hogarth (1989b).

Venture theory

Success with the ambiguity model suggested that the proposed, underlying cognitive processes might also apply to judgments and choice in cases for which ambiguity was absent. This insight led to the development of venture theory (Hogarth & Einhorn, 1990a).

Venture theory is a generalization of the well-known prospect theory model developed by Kahneman and Tversky (1979). The generalization takes the form of providing an explicit psychological model for the prospect theory decision weight function. In brief, the model assumes

that, even in the presence of known probabilities, people will engage in a mental simulation process similar to that assumed in the ambiguity model. Moreover, because this simulation is affected by both the sign and size of payoffs, the "decision weight" function will differ depending on the values of both of these variables (see also description of the ambiguity model, above). When these assumptions concerning the decision weight function (for details see Hogarth & Einhorn, 1990a) are combined with the properties of the prospect theory value function, it is possible to obtain a series of predictions concerning effects on attitudes toward risk and ambiguity that are induced by different levels of both probabilities and payoffs as well as the sign of the latter. These predictions are important in that they indicate the conditions under which payoffs and probabilities do and do not interact in their effects on revealed attitudes toward risk and ambiguity. Indeed, venture theory provides one of the first, explicit, theoretical treatments of this issue that is derived from psychological as opposed to mathematical/economic reasoning.

Venture theory's predictions were tested in a series of three experiments (see Hogarth & Einhorn, 1990a). Two of the experiments involved choices using hypothetical gambles and one involved gambles with real payoffs. One interesting result of the experiments was that although almost all of venture theory's 14 predictions were validated in the experiment involving real payoffs, for the hypothetical payoffs the rate of agreement was not so high. In particular, attitudes toward risk and ambiguity seem to differ in the domain of losses when payoffs are real as opposed to hypothetical. Parenthetically, the two venture theory predictions that were not upheld in the real payoff experiment concerned the nature of probability x payoff interactions in attitudes toward risk and ambiguity for losses. That is, although these interactions were observed, their precise form was not that predicted by venture theory.

Finally, the above tests of venture theory suffer from the fact that they occur in the confines of the psychological laboratory. Unfortunately, an important cost of doing research on risky decision making is that any new models proposed must be shown to be able to explain the large experimental literature even though many researchers now believe that the gambling metaphor of risky decision making is incomplete, and that work must be conducted in more ecologically relevant settings. The advantage of venture theory is that it explicitly models how key

psychological constructs of emotion (e.g., caution) and cognition (e.g., imagination) affect decision weights. It therefore offers a useful structure for studying the impact of uncertainty both in and outside the psychological laboratory.

Decision making under ignorance

The domain of venture theory is decisions under risk and ambiguity. But, how do people make decisions when they have no or very little information about probabilities or payoffs, i.e., under conditions of ignorance? For example, imagine that you have just purchased a VCR. The salesperson now asks whether you would like to buy an extended warranty agreement for, say, $40. How do you evaluate this decision if (a) you have little idea of the chance of incurring a breakdown nor (b) how much repairs would cost?

One way people might handle this kind of situation could be to generate arguments with themselves that would either favor or be against buying the warranty (or both). For example, one argument might be "Don't buy because these are not usually good deals." Another could be "Buy because if you don't, you might regret it in the case of a breakdown."

Our latest work (conducted together with Howard Kunreuther at the University of Pennsylvania) has begun to explore "decision making under ignorance" using this arguments framework. So far, we have conducted two preliminary studies using the warranty purchase decision as a paradigmatic case. The basic experimental design involves presenting subjects with warranty scenarios and then asking for both a decision (buy or not buy) and the arguments used in reaching the decision (either in a "free" format or by checking off a list of preestablished arguments). Our preliminary results may be summarized briefly as follows:

(1) people try to focus on numbers in the problems if they can. For example, most subjects seem to compare the cost of the warranty to the cost of the product.

(2) people's arguments in these situations are quite close to what one would expect from a rational analysis of the problem. For example, arguments are frequently centered on assessing the likelihood of breakdown and/or involve tradeoffs, e.g., feelings of "risk" versus cost of warranty.

(3) most arguments are focussed on evaluating specifics of the particular cases as opposed

to involving more general principles such as "I never buy these kinds of warranties."

More work on the topic of the use of arguments is currently under way.

Belief Updating

The previous report (Einhorn & Hogarth, 1987) described work on a model of belief updating. There has been considerable progress on this work during the reporting period. Because this work is fully detailed in Hogarth and Einhorn (1990b), this section only summarizes the main points.

The theory of belief updating represents a concise, descriptive account of the manner in which beliefs are updated in response to information that is received sequentially. To validate this model, we have chosen to focus on the phenomena of order effects, i.e., the fact the order in which information is received can affect the level of the final opinion. These order effects are seen as arising from the interaction of information-processing strategies and task characteristics. Based on an extensive review of the literature (involving some 60 different papers), the following task variables were identified as key: (1) complexity of the stimuli processed for each revision of belief; (2) length of the series of evidence items processed; and (3) response mode (whether responses are made in response to each piece of evidence, i.e., Step-by-Step, or only after all evidence has been processed, i.e., End-of-Sequence). The model itself assumes that people handle belief-updating tasks by a general, sequential anchoring-and-adjustment process in which current opinion, or the anchor, is adjusted by the impact of succeeding pieces of evidence.

In algebraic terms, the model can be written

$$S_k = S_{k-1} + w_k\,[s(x_k) - R] \qquad (2)$$

where S_k = degree of belief in some hypothesis, impression or attitude after evaluating k pieces of evidence ($0 \le S_k \le 1$).

S_{k-1} = anchor or prior opinion. The initial strength of belief is denoted S_0.

$s(x_k)$ = subjective evaluation of the kth piece of evidence. (Different people may accord the same evidence, x_k, different evaluations).

R = the reference point or background against which the impact of the kth piece of evidence is evaluated.

w_k = the adjustment weight for the kth piece of evidence ($0 \leq w_k \leq 1$).

Within this general model there are three important subprocesses which concern (a) how evidence is encoded -- this can be done in two ways, either as a deviation relative to the size of the preceding anchor (operationalized by setting $R = S_{k-1}$) or as positive or negative vis-à-vis the hypothesis under consideration (operationalized by setting $R = 0$). The former, labeled estimation mode, results in data consistent with averaging models of judgment; the latter, labeled evaluation mode, implies adding models; (b) how evidence is processed -- whether beliefs are revised in response to each piece of evidence (i.e., a Step-by-Step *strategy*) or only after all the evidence has been processed (i.e., an End-of-Sequence *strategy*), and (c) how the adjustment is accomplished-- a contrast assumption is adopted in which w_k is taken to be proportional to S_{k-1}.

The theory specifies conditions under which (a) evidence is encoded in estimation or evaluation modes, and (b) use is made of the Step-by-Step or End-of-Sequence processing strategies. This analysis is shown to account for much existing data and to make novel predictions for combinations of task characteristics where current data are sparse.

Whereas several experiments on order effects had been conducted at the time of the previous report (Einhorn & Hogarth, 1987), one important new experiment reported in this paper dealt with a manipulation of the manner in which evidence was encoded. This experiment showed that when the same evidence was presented in alternative forms, intended to evoke alternatively the estimation and evaluation modes, order effects were affected. We believe this is a particularly important result for two reasons: (1) whereas there has been considerable confusion in the literature concerning whether people use averaging or adding models of judgment, our theory explains how the same processes can produce both types of data depending on how information is encoded.

Moreover, in some cases order effects are induced by the manner in which information is encoded as opposed to the manner by which it is processed; and (2) we have also provided an explicit experimental demonstration of our theoretical hypothesis.

Exactingness and Incentives

Learning from feedback is a critical dimension of decision making. Feedback, however, is often ambiguous. In particular, we note that feedback from the outcomes of decisions can serve two functions that are often confounded. One function is inferential. Feedback informs the decision maker about the structure of the underlying task. For example, when a student writes a paper, feedback in the form of a grade provides information about how to write a good paper. The second function is evaluative. To continue the example, feedback also provides information about the student's performance. Was this good or bad? Note, however, that the feedback -- in this case a grade -- is confounded. To what extent does the grade reflect the student's ability to write papers, and to what extent does it reflect the teacher's grading policy?

Evaluation of decision-making performance can differ on a dimension that we term the *exactingness* of the environment and which reflects the severity of penalties imposed for errors. Tasks are *exacting* to the extent that deviations from optimal decisions are heavily punished, and *lenient* to the extent that they are not.

In addition to exactingness, decision-making tasks can vary in the extent to which different levels of performance have consequences for the decision maker. In the case of the student essay, for example, the student may or may not perceive the grade as consequential (e.g., by affecting chances of admission to graduate school). In other words, tasks can vary in the extent to which decision makers have incentives to perform well.

The present work examined the effects of both exactingness and incentives. There are several reasons for studying these phenomena together. First, to know when and how exactingness and incentives affect learning is important at a practical level. In business or the

military, for example, what levels of exactingness implied by different evaluation schemes promote efficient learning? Do real consequences in terms, say, of money or lives help people learn to make decisions more effectively? If exactingness and/or incentives are detrimental, how can learning be structured to overcome these impediments? Second, despite the importance of exactingness in many real-world tasks, little theoretical attention has been directed toward understanding its effects. Third, and also from a theoretical viewpoint, controversy exists as to whether incentives necessarily improve performance. From naive behaviorist or economic viewpoints, for example, one could argue that incentives will always improve performance and much evidence is consistent with this contention. However, there is also evidence that under some conditions incentives can be detrimental.

Theoretical analysis. We hypothesize that exactingness induces forces that have both positive and negative effects on performance when learning to make decisions in a repetitive task.

The positive aspect of increases in exactingness lies in the opportunities it provides for learning. To see this, imagine a situation which is perfectly "lenient." In this case, people always receive perfect outcomes no matter what decisions they take. They can therefore never learn how the actions they take are related to objective criteria. As the environment becomes more exacting, however, outcomes become more sensitive to "errors" in decisions thereby providing greater possibilities for learning. Learning, however, would not be expected to increase linearly with exactingness. Instead, we hypothesize that the positive aspect of learning (as measured by performance) is an increasing, concave function of exactingness.

The main negative aspect associated with increases in exactingness lies in the interpretation of feedback and subsequent reactions to this. Specifically, as exactingness increases, feedback in is increasingly liable to be negative and, in the absence of alternative points of reference, perceived as such. In learning environments, people are likely to react differently to positive and negative feedback. Whereas positive feedback reinforces maintaining and refining existing behavior or response strategies, negative feedback encourages shifting strategies and seeking alternatives that may work better. Because the subset of response strategies that "work" in exacting environments is

much smaller than those that don't, continual shifting of strategies results in lower performance -- at least in the short run. We hypothesize that as exactingness increases, the rate at which this negative factor affects learning does not decrease. Thus, the negative aspect of learning (as measured by performance) is a non-concave decreasing function of exactingness.

We propose that incentives accentuate both the positive and negative forces of exactingness. More specifically, when feedback is generally positive, as in lenient environments, incentives will induce more consistent application of apparently successful response strategies and performance will improve. When feedback is generally negative, as in exacting environments, incentives will induce more intensive search for alternatives, and performance will degrade, at least in the short run.

A formal model. To clarify implications of the above arguments, we use the heuristic device of a simple, algebraic model. Let

$$\pi = k\,[b\,\alpha^{\lambda} - c\,\alpha] \tag{3}$$

where π represents performance, k is a constant of proportionality, α represents exactingness ($\alpha > 0$), b and c are coefficients (b, c > 0) representing the extent to which the presence of incentives accentuates, respectively, the positive and negative aspects of exactingness (α) on performance (π), and λ ($0 < \lambda < 1$) determines the degree of concavity of the function that represents the positive aspect of exactingness (α) on performance.

We draw two general implications from this model. First, the form of Equation 3 is such that performance will be a single-peaked (inverted-U shaped) function of exactingness (α). This means that performance will be better when exactingness (α) is at intermediate rather than extreme values.

Second, we can enquire about how incentives interact with exactingness. To do so, assume that Equation 3 represents performance with no incentives and denote performance with incentives

by

$$\pi' = k\,[b'\alpha^{\lambda} - c'\alpha] \qquad (4)$$

where $b' > b$ and $c' > c$. Next, ask when performance with incentives exceeds that without, i.e., when $\pi' > \pi$. Simple algebraic manipulation leads to the condition

$$(b' - b)/(c' - c) > \alpha^{1-\lambda} \qquad (5)$$

The general implication of (5) is that there is a critical value of exactingness (α) below which incentives lead to superior performance but above which incentives are dysfunctional.

Predictions. The model implied by Equation 3 and its underlying assumptions lead to several predictions concerning observed performance (π).

Prediction 1: Environments characterized by intermediate levels of exactingness (α) will lead to better performance (π) than lenient or exacting environments. (This is implied by the fact that π is a single-peaked or inverted-U shaped function of α.)

Prediction 2: There will be an interaction between incentives and exactingness. Whereas incentives will lead to improved performance in lenient environments, they will become less beneficial as exactingness increases.

Prediction 3: If the negative effects of exactingness (α) on performance (π) are eliminated, performance (π) should increase as a function of exactingness (α).

Experimental results. The above model and hypotheses were tested in a series of five experiments -- see Hogarth, Gibbs, McKenzie & Marquis (in press) for details. The experiments were based on a repetitive decision making task that was similar to a single-cue probability learning task except that feedback was not in the form of observations of a criterion variable. Instead,

feedback was by way of "evaluation points" and subjects were instructed to maximize evaluation points. Unknown to the subjects, evaluation points were inversely proportional to squared prediction errors, with the constant of proportionality being used to manipulate exactingness. "Lenient" environments were characterized by small proportionality constants and "exacting" environments by large ones.

The main results of the experiments were as follows:

(1) Learning -- as measured by performance -- was seen to be an inverted-U shaped function of exactingness. This is illustrated in Figure 2 below which shows performance as a function of three levels of exactingness (lenient, intermediate, and exacting) over two rounds of one of our experiments each involving 30 trials -- Prediction 1.

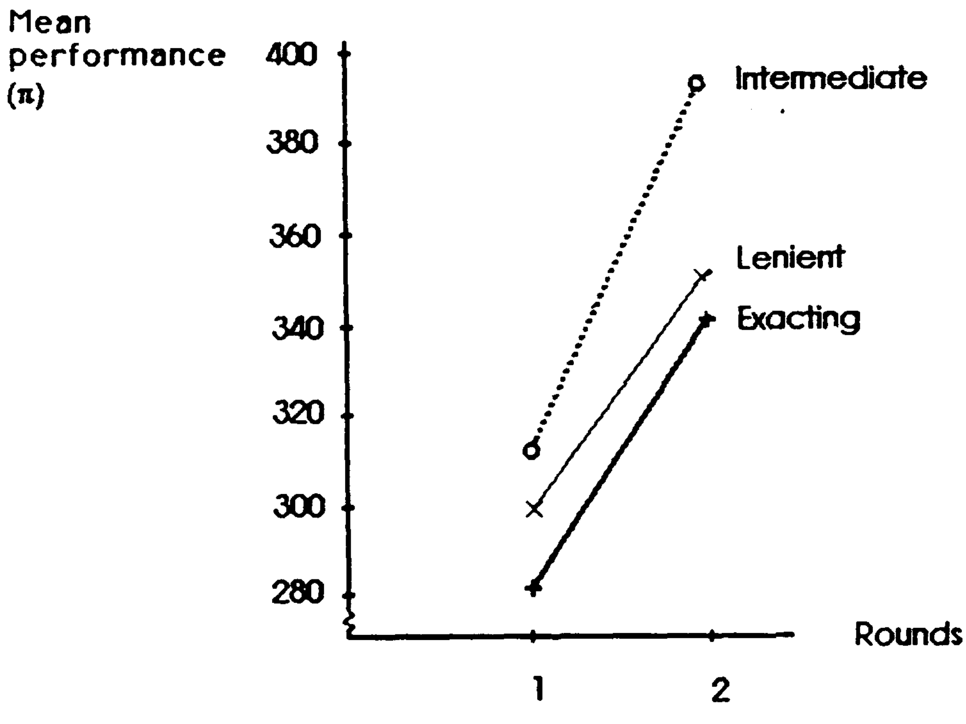

Figure 2: Mean performance (π) by types of environment (lenient, intermediate, and exacting) across rounds.

(2) There was an interaction between incentives and exactingness. Whereas performance was better with rather than without explicit monetary incentives in a lenient environment, this relationship reversed in the exacting environment (there was no differential effect in an intermediate environment). This result held in a condition where the incentive function was "sharp " (i.e., distinguished clearly between successful and unsuccessful performance) and where incentives were manipulated by aspirations as opposed to external, monetary incentives -- Prediction 2. In the case of a "flat" incentive function (i.e., which did not distinguish sharply between different levels of performance), however, incentives had no differential effect on performance.

(3) When the negative effects of exactingness were mitigated (by providing subjects both outcome feedback and evaluation points), performance increased with exactingness -- Prediction 3.

(4) Comparisons were made of performance under incentives after subjects had been trained under different conditions of incentives and exactingness. In terms of performance, the most effective methods were found to be either (a) training under conditions where subjects were told to try to learn the task as opposed to maximize evaluation points and (b) training under intermediate conditions of exactingness (but under instructions to maximize evaluation points). The former method, however, took much more time than the latter.

(5) Questionnaires were constructed to test subjects' ability to articulate their understanding of the task environment (over and above their ability to predict outcomes). Results of these tests were highly predictive of subjects' individual performance on the task and were also related to the experimental manipulations.

We believe that both the theory and experimental results achieved in this study are very important. In many decision-making tasks feedback is ambiguous with the result that people are often ignorant of whether decisions are taken in environments that are "lenient" or "exacting" and the effects this can have on their ability to learn. Indeed, the fact that our experiments generated such a complex pattern of outcomes given the small nature of the manipulation (i.e., adjusting exactingness) was remarkable. In addition, the effects of incentives on performance have often been puzzling, to say the least.

Technical Reports

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19. Einhorn, H. J., & Hogarth, R. M. (1987). A theory of diagnostic inference: Contract progress report. University of Chicago, Center for Decision Research, AD #179786.

20. Einhorn, H. J., & Hogarth, R. M. (1987 October). Adaptation and inertia in belief updating: The contrast-inertia model. University of Chicago, Center for Decision Research.

21. Hogarth, R. M., & Einhorn, H. J. (1988 January). Venture theory: A model of decision weights. University of Chicago, Center for Decision Research, AD #A194809.

22. Hogarth, R. M. (1988 May). Ambiguity and competitive decision making: Some implications and tests. University of Chicago, Center for Decision Research, AD #A196149.

23. Hogarth, R. M., & Kunreuther, H. (1988 November). Pricing insurance and warranties: Ambiguity and correlated risks. University of Chicago, Center for Decision Research, AD #A203773.

24. Hogarth, R. M., Gibbs, B. J., McKenzie, C. R. M., Marquis, M. A. (1989 June). Learning to make decisions: When incentives help and hinder. University of Chicago, Center for Decision Research, AD #A210185.

25. Hogarth, R. M., & Kunreuther, H. (1990 May). Decision making under uncertainty: The effects of role and ambiguity. University of Chicago, Center for Decision Research, AD #A225771.

26. Kunreuther, H., & Hogarth, R. M. (1990 May). How does ambiguity affect insurance decisions? University of Chicago, Center for Decision Research, AD #A225707.

Publications

Einhorn, H. J., & Hogarth, R. M. (1987). Decision making: Going forward in reverse. *Harvard Business Review*, 65(1), 66-70.

Goldstein, W. M., & Einhorn, H. J. (1987). Expression theory and the preference reversal phenomena. *Psychological Review*, *94*(2), 236-254.

Hogarth, R. M. (1987). *Judgement and choice: The psychology of decision.* (2nd ed.) Chichester, UK: Wiley.

Hogarth, R. M., & Reder, M. W. (Eds.) (1987). *Rational choice: The contrast between economics and psychology.* Chicago: University of Chicago Press.

Simon, H. A., et al. (1987). Decision making and problem solving. *Interfaces*, *17(5)*, 11-31. (Reprinted from "Report of the Research Briefing Panel on Decision Making and Problem Solving" in Research Briefings 1986, Washington, DC: National Academy Press.)

Einhorn, H. J. (1988). Diagnosis and causality in clinical and statistical prediction. In D. C. Turk & P. Salovey (Eds.), *Reasoning, inference, and judgment in clinical psychology*, 51-70. New York: The Free Press.

Einhorn, H. J., & Hogarth, R. M. (1988). Decision making under ambiguity: A note. In B. Munier (Ed.), *Risk, decision and rationality*, 327-336. Dordrecht, Holland: D. Reidel Publishing Company.

Hogarth, R. M., & Klayman, J. (1988). Hillel J. Einhorn (1941-1987). [Obituary]. *American Psychologist*, *43*, 656.

Hogarth, R. M., & Makridakis, S. (1988). Consider the principal finding: A reply to William T. Ross. *Management Science*, *34(5)*, 672-673.

de Wit, H., Hogarth, R. M., Koehler, J. J., & Luchins, D. J. (1989). Effects of diazepam on a belief-updating task. *Psychological Reports*, *64*, 219-226.

Goldstein, W. M., & Einhorn, H. J. (1989). Expression theory and the measurement of apparently labile values. *Annals of Operations Research*, *19*, 51-78.

Hogarth, R. M. (1989a). On combining diagnostic 'forecasts': Thoughts and some evidence. *International Journal of Forecasting*, *5*, 593-597.

Hogarth, R. M. (1989b). Ambiguity and competitive decision making: Some implications and tests. In P. C. Fishburn & I. H. LaValle (eds.), *Annals of Operations Research*, *19*, 31-50.

Hogarth, R. M. (1989c). Transgressive action and inaction: The need to study both. *Acta Psychologica*, *70*, 65-69 (invited commentary).

Hogarth, R. M., & Kunreuther, H. (1989). Risk, ambiguity, and insurance. *Journal of Risk and Uncertainty*, *2*, 5-35.

Klayman, J., & Hogarth, R. M. (1989). Does ECHO explain explanation? A psychological perspective. *The Behavioral and Brain Sciences*, *12(3)*, 478-479 (invited commentary).

Hogarth, R. M. (Ed.) (1990). *Insights in decision making: A tribute to Hillel J. Einhorn.* Chicago: The University of Chicago Press.

Hogarth, R. M., & Einhorn, H. J. (1990a). Venture theory: A model of decision weights. *Management Science*, *36(7)*, 780-803.

Hogarth, R. M., & Einhorn, H. J. (1990b May). *Order effects in belief updating: The belief-adjustment model.* University of Chicago, Graduate School of Business, Center for Decision Research.

Hogarth, R. M., Gibbs, B. J., McKenzie, C. R. M., & Marquis, M. A. (in press). Learning from feedback: Exactingness and incentives. *Journal of Experimental Psychology: Learning, Memory, and Cognition.*

Hogarth, R. M., & Kunreuther, H. (1990 October). *Pricing insurance and warranties: Ambiguity and correlated risks.* University of Chicago, Center for Decision Research.

Hogarth, R. M., & Kunreuther, H. (in press). Decision making under uncertainty: The effects of role and ambiguity. In F. Heller (Ed.), *Decision making and leadership.* Cambridge, England: Cambridge University Press.

Kunreuther, H., & Hogarth, R. M. (in press). How does ambiguity affect insurance decisions? In G. Dionne (Ed.), *Insurance economics.* Boston: Kluwer.

References in report not included in above lists

Hogarth, R. M. (1986). Generalization in decision research: The role of formal models. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-16*, 439-449.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263-291.

Ph. D. Theses

Gibbs, B. J. (1991, expected). *Variable tastes: Self-manipulation of stimulus valuations.* Unpublished doctoral dissertation, University of Chicago.

Koehler, J. J. (1989). *Judgments of evidence quality among scientists as a function of prior beliefs and commitments.* Unpublished doctoral dissertation, University of Chicago

Maines, L. (1990). *Data redundancy and consensus forecasting judgments.* Unpublished doctoral dissertation, University of Chicago

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George Mason University
4400 University Drive
Fairfax, Virginia 22030

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